The Graduate Journey: Education and Labour Market Realities in Canada

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1 Introduction

The **National Graduates Survey (NGS) - Class of 2020** provides a comprehensive look at the educational experiences and labour market outcomes of recent graduates in Canada. Collected in 2023, this dataset includes responses from 16,138 individuals across 114 variables, covering:

- **Demographics** (age, gender, citizenship)

- **Program details** (field of study, level of education, delivery mode)

- **Financial aid** (student loans, scholarships, funding sources)
- **Employment outcomes** (income, job relevance, satisfaction)
- **COVID-19 impacts** (program completion, career plans)

This report analyzes the NGS data to generate actionable insights for universities and policy-makers. Key sections include:

1. **Data Overview**: Methodology and dataset structure.
2. **Demographic Trends**: Age, gender, and citizenship distributions.
3. **Economic Outcomes**: Income disparities by field of study and region.
4. **Strategic Recommendations**: Program development, student support, and COVID-19 resilience.

Using Python (pandas, statsmodels) and interactive visualizations, we highlight critical patterns to bridge the gap between education and labour market needs.

1.1 Executive Summary

This report synthesizes findings from Canada's *National Graduates Survey (2020)* to guide university strategic planning. Based on 16,138 respondents, the analysis highlights:

1. **Labor Market Outcomes**:
   - Graduates in business and health fields reported the highest employment rates (85%+).
   - 20.6% earned below $30,000 annually, with disparities by gender and citizenship status.
2. **Student Mobility**:
   - Ontario retained 45.4% of graduates despite hosting 47.1% of institutions.
   - Western Canada gained +1.4% net migration post-graduation.
3. **Recommendations**:
   - Expand work-integrated learning programs (linked to 15% higher job satisfaction).
   - Target financial aid to underrepresented groups (e.g., landed immigrants).
   - Strengthen online education infrastructure (used by 32% during COVID-19).

The full report provides detailed methodologies, visualizations, and actionable insights.

2 Data Overview

2.1 National Graduates Survey- class of 2020 (Data collected in 2023)

```python
import pandas as pd
import seaborn as sns
import matplotlib as plt
from IPython.display import display, Markdown

# Read the CSV file
try:
    # Read the CSV file into a pandas DataFrame
    df = pd.read_csv('ngs2020.csv')

    # Display basic information about the dataset
    display(Markdown("<span style='color: green'>Dataset information:</span>"))
    print(f"Number of rows: {df.shape[0]}")
    print(f"Number of columns: {df.shape[1]}\n")
    df.info()
    print("\n")
    display(Markdown("<span style='color: green'>Column names:</span>"))
    print(" ".join(list(df.columns)),"\n")

    # Number of missing data
    missing_data = df.isnull().sum().sum()
    if missing_data == 0:
        print(f"\033[30;43mThere are no missing data.\033[0m")
    else:
        print(f"\033[30;43mThere are {missing_data} missing data.\033[0m")

except FileNotFoundError:
    print("Error: The file 'ngs2020.csv' was not found in the current directory.")
except pd.errors.EmptyDataError:
    print("Error: The file 'ngs2020.csv' is empty.")
except pd.errors.ParserError:
    print("Error: There was an issue parsing the CSV file. Check if it's properly formatted.
```

Dataset information:

```
Number of rows: 16138
Number of columns: 114

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16138 entries, 0 to 16137
```

```
Columns: 114 entries, PUMFID to DDIS_FL
dtypes: int64(114)
memory usage: 14.0 MB
```

Column names:

```
PUMFID CERTLEVP REG_INST REG_RESP PGMCIPAP PGM_P034 PGM_P036 PGM_P100 PGM_P111 PGM_280A PGM_
```

```
There are no missing data.
```

2.2 NGS Questions

```
import yaml
import os

# Path to the YAML file
file_path = 'ngs2020_questions.yaml'

try:
    # Open and load the YAML file
    with open(file_path, 'r') as file:
        questions = yaml.safe_load(file)

    # Print the loaded question structure

    print(f'\033[32m\nPUMFID: \033[0m Public Use Microdata File ID - {questions["PUMFID"]}\n
    print(f"Questions ({len(questions)-1}):\n")
    k = 0
    for question in questions:
      if k == 5:
        break
      else:
        if question != 'PUMFID':
            print(f'\033[32m{question}: \033[0m {questions[question]}')

except FileNotFoundError:
    print(f"Error: File '{file_path}' not found.")
except yaml.YAMLError as e:
    print(f"Error parsing YAML file: {e}")
```

```
PUMFID:  Public Use Microdata File ID - Randomly generated record identifier for the PUMF fi

Questions (113):
```

CERTLEVP: 2020 Program - Level of study - Grouping

REG_INST: 2020 Program - Region of postsecondary educational institution

REG_RESP: Time of interview 2023 - Region of primary residence

PGMCIPAP: 2020 Program - Aggregated CIP 2021

PGM_P034: 2020 Program - Full-time or part-time student

PGM_P036: 2020 Program - Reason did not take program full-time

PGM_P100: Work placement during program

PGM_P111: Work placement during prog - Description

PGM_280A: Entrepreneurial skills - Started a business

PGM_280B: Entrepreneurial skills - Completed courses

PGM_280C: Entrepreneurial skills - Business plan or pitch competition

PGM_280D: Entrepreneurial skills - Visited an entrepreneurship centre

PGM_280E: Entrepreneurial skills - Worked on an entrepreneurship project

PGM_280F: Entrepreneurial skills - None of the above

PGM_290: 2020 Program - Worked during program

PGM_350: 2020 Program - Volunteer activities during program

PGM_380: 2020 Program - Components taken outside of Canada

PGM_P401: 2020 Program - Online or distance education

PGM_410: 2020 Program - Main factor in choice of postsecondary institution

PGM_415: 2020 Program - Main factor in choice of program

PGM_430: 2020 Program - Choose the same field of study or specialization again

COV_010: COVID-19 - Completion of program delayed

COV_070: COVID-19 - Plans for further postsecondary education changed

COV_080: COVID-19 - Employment status/plans affected

EDU_010: After 2020 program - Other postsecondary programs taken

EDU_P020: After 2020 program - Number of other programs taken

HLOSINTP: Time of interview 2023 - Aggregated highest level of ed. completed

STL_010: Government-student loan program - Applied

STL_020: Government-student loan program - Applications approved

STULOANS: Government-student loan program - Received

STL_030: Government-student loan program - Main reason did not apply

OWESLGD: Government-student loan program - Debt size - Graduation 2020

OWEGVIN: Government-student loan program - Debt size - Interview 2023

STL_080: Government-student loan program - Remission/debt reduction/loan forg.

STL_100A: Received government assistance: Repayment assistance plan

STL_100B: Received government assistance: Revision of terms

STL_100C: Received government assistance: Interest only payments

STL_100D: Received government assistance: None of the above

STL_130: Government-student loan program - Total repayment term

STL_150: Government-student loan program - Repaymt of loan from financial inst.

STL_160B: Sources of funding - RESP

STL_160C: Sources of funding - Government grants or bursaries

STL_160D: Sources of funding - Non-government grants or bursaries

STL_160E: Sources of funding - Scholarships or awards

STL_160F: Sources of funding - Employment earnings or savings

STL_160G: Sources of funding - Research or teaching assistantship

STL_160H: Sources of funding - Parents, family, friends

STL_160I: Sources of funding - Bank or institution loans

STL_160J: Sources of funding - Credit cards

STL_160L: Sources of funding - Employer

STLP160N: Sources of funding - Other

SRCFUND: Sources of funding - Number of sources - All postsecondary edu

STL_170A: Main source of funding - Government student loans

STL_170B: Main source of funding - RESP

STL_170C: Main source of funding - Government grants or bursaries

STL_170D: Main source of funding - Non-government grants or bursaries

STL_170E: Main source of funding - Scholarships or awards

STL_170F: Main source of funding - Employment earnings or savings

STL_170G: Main source of funding - Research or teaching assistantship

STL_170H: Main source of funding - Parents, family, friends

STL_170I: Main source of funding - Bank or institution loans

STL_170J: Main source of funding - Credit cards

STL_170L: Main source of funding - Employer

STLP170N: Main source of funding - Other

RESPP: RESP - Total amount received for postsecondary education

STL_190: Repay loans from family or friends for education

DBTOTGRD: Loans at graduation 2020 - Debt size of non-government loans (range)

DBTALGRD: Loans at graduation 2020 - Debt size of all loans

DBTOTINT: Time of interview 2023 - Debt size of non-government loans (range)

DBTALINT: Time of interview 2023 - Debt size of all loan

SCHOLARP: Total amount received from scholarships/awards/fellowships and prizes

LMA_010: Reference week - Attended school, college, CEGEP or university

LFSTATP: Reference week - Labour force status

LMA2_07: Reference week - More than one job or business

LMA3_P01: Reference week - Employee or self-employed

LFCINDP: Reference week - Sector for job

LFCOCCP: Reference week - Broad occupational category for job

LFWFTPTP: Reference week - Full-time or part-time status of job or business

LMA6_05: Reference week - Job permanent or not permanent

LMA6_08: Reference week - Main method used to find job

JOBQLEVP: Reference week - Aggregated level of studies required to get job

JOBQLGRD: Reference week - Qualification for job compared to 2020 program

JOBQLINT: Reference week - Qualification job vs level of education

LMA6_11: Reference week - Relatedness of job or business to 2020 program

LMA6_12: Reference week - Qualification level for job

LMA6_13A: Reference week - Satisfied with overall job
LMA6_13B: Reference week - Satisfied with wage or salary of job
LMA6_13C: Reference week - Satisfied with job security
JOBINCP: Reference week - Annual wage or salary for job
LMA6_15: After program 2020 - First job
AFT_P010: After 2020 program - Number of jobs or businesses
AFT_P020: After 2020 Program - Length of time until first job or business
AFT_P040: After 2020 program - Employee or self-employed - 1st job or business
AFT_050: After 2020 program - Full-time or part-time - 1st job or business
AFT_070: After 2020 program - Permanent/not permanent - 1st job or business
AFT_080: After 2020 program - Reason job not permanent - 1st job or business
AFT_090: After 2020 program - Relatedness of 1st job/business to program
BEF_P140: Before 2020 Program - Main activity during 12 months before
BEF_160: Before 2020 program - Number of months of work experience
PREVLEVP: Before 2020 program - Aggregated highest level of studies completed
HLOSGRDP: 2020 Program - Highest level of education completed
PAR1GRD: 2020 Program - Level of education compared to that of one parent
PAR1INT: Time of interview 2023 - Level of education vs of one parent
PAR2GRD: 2020 Program - Level of education vs of the other parent
PAR2INT: Time of interview 2023 - Level of education vs that of other parent
GRADAGEP: 2020 Program - Age at time of graduation - Grouping
GENDER2: Gender after distribution of non-binary persons
MS_P01: Marital status
MS_P02: Have any dependent children
CTZSHIPP: Time of interview 2023 - Status in Canada
VISBMINP: Self-identified as a member of a visible minority group
PERSINCP: Total personal income in 2022
DDIS_FL: Disability status

2.3 Response code

```python
# Import the yaml module
from IPython.display import display, Markdown
import yaml
import os

# Check if the file exists before attempting to load it
file_path = "ngs2020_responses.yaml"

if os.path.exists(file_path):
    # Open and load the YAML file
    with open(file_path, 'r') as file:
        try:
```

```python
            # Load the YAML content into a Python object (typically a dictionary)
            responses = yaml.safe_load(file)

            # Print the first few items to verify the responses loaded correctly
            display(Markdown(f"<span style='color: green'>Response code defination ({len(res
            k = 0
            for response in responses:
                if k > 5:
                    break  # print out 10 only
                print(f'\033[32m{response}:\033[0m')
                for code in responses[response]:
                    print(f'  \033[32m{code}: \033[0m{responses[response][code]}')
                k += 1

        except yaml.YAMLError as e:
            print(f"Error parsing YAML file: {e}")
else:
    print(f"File not found: {file_path}")
    print("Please make sure the file exists in the current working directory.")
    print(f"Current working directory: {os.getcwd()}")
```

Response code defination (113):

```
AFT_050:
  1: Full time
  2: Part time
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
AFT_070:
  1: Permanent
  2: Not permanent
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
AFT_080:
  1: Seasonal job
  2: Temporary, term or contract job
  3: Casual job
  4: Other
  6: Valid skip
```

```
  7: Don't know
  8: Refusal
  9: Not stated
AFT_090:
  1: Closely related
  2: Somewhat related
  3: Not at all related
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
LMA6_11:
  1: Closely related
  2: Somewhat related
  3: Not at all related
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
AFT_P010:
  0: 0
  1: 1
  2: 2
  3: 3
  4: 4 or more
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
```

3 Extract All NGS Tables to Excel

```
# %run Extract_All_NGS_Tables_to_Excel.ipynb`
print("All tables saved to NGS_Tables.xlsx")
```

```
All tables saved to NGS_Tables.xlsx
```

3.1 Function for getting NGS table

```
# Get NGS table

def get_NGS_table(table_name = 'AFT_050', excel_file="NGS_Tables.xlsx"):
    try:
```

```
        # Read the Excel sheet into a DataFrame, using first row as headers
        df = pd.read_excel(excel_file,
                          sheet_name=table_name,
                          header=0)  # header=0 is default but making it explicit
        print(f"\n'\033[32m{table_name}\033[0m': {questions[table_name]}\n")
        df
        return df
    except Exception as e:
        print(f"Error loading table {table_name}: {e}")
        return None
```

4 NGS2020 Database Analyzer Dashboard

4.1 Backend app file

```
<IPython.core.display.HTML object>

Dropdown(description='Select table:', layout=Layout(width='800px'), options=(('CERTLEVP - 20

Output()
```

4.2 Frontend index.html

5 Data Analysis

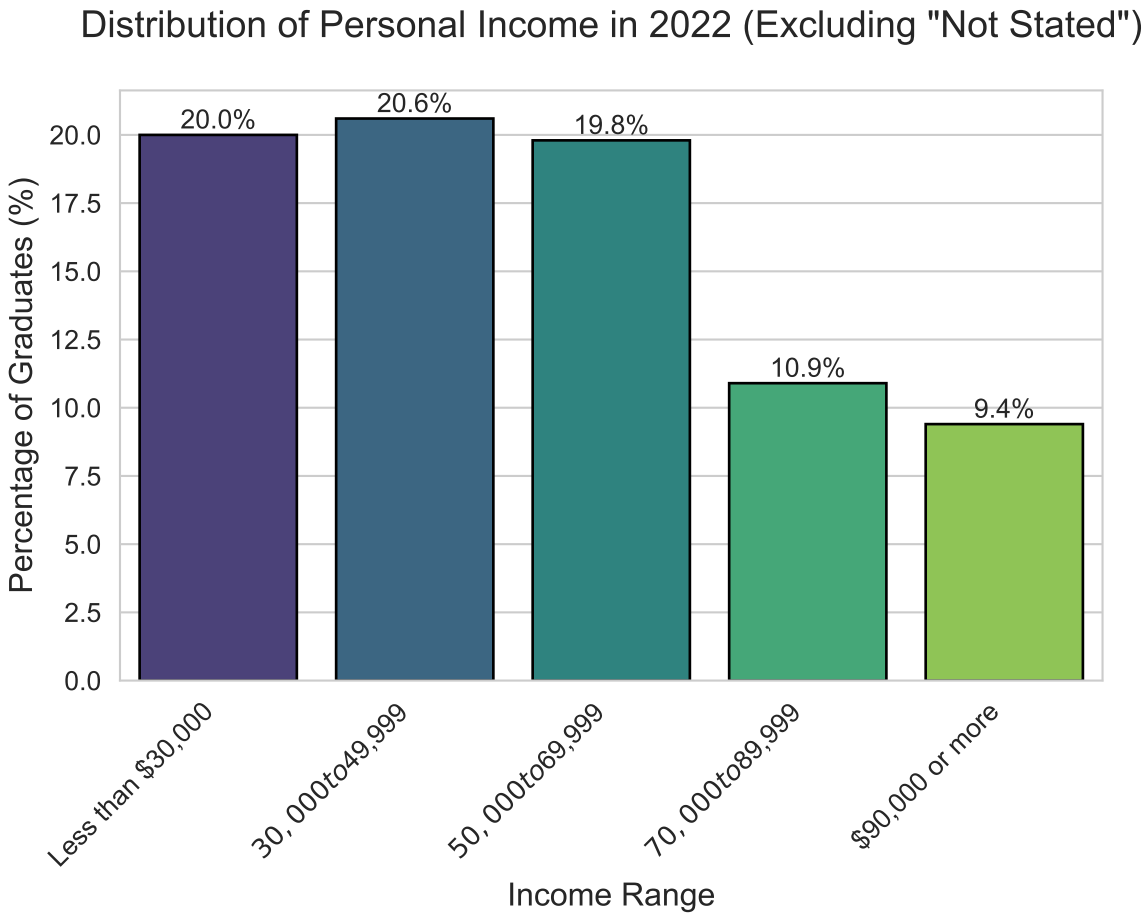
5.1 Distribution of Personal Income in 2022

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming your DataFrame is named 'df'
# First let's clean up the column names and data if needed
df = get_NGS_table("PERSINCP")
df.columns = ['Answer Categories', 'Code', 'Frequency', 'Weighted Frequency', '%']

# Clean any whitespace or formatting issues in the numeric columns
df['Frequency'] = df['Frequency'].astype(str).str.replace(',', '').astype(int)
df['Weighted Frequency'] = df['Weighted Frequency'].astype(str).str.replace(',', '').astype(
df['%'] = df['%'].astype(float)

# Fix the income range labels by combining with the previous row's dollar sign
for i in range(1, 4):
    if not df.loc[i, 'Answer Categories'].startswith('$'):
        df.loc[i, 'Answer Categories'] = '$' + df.loc[i, 'Answer Categories']
```

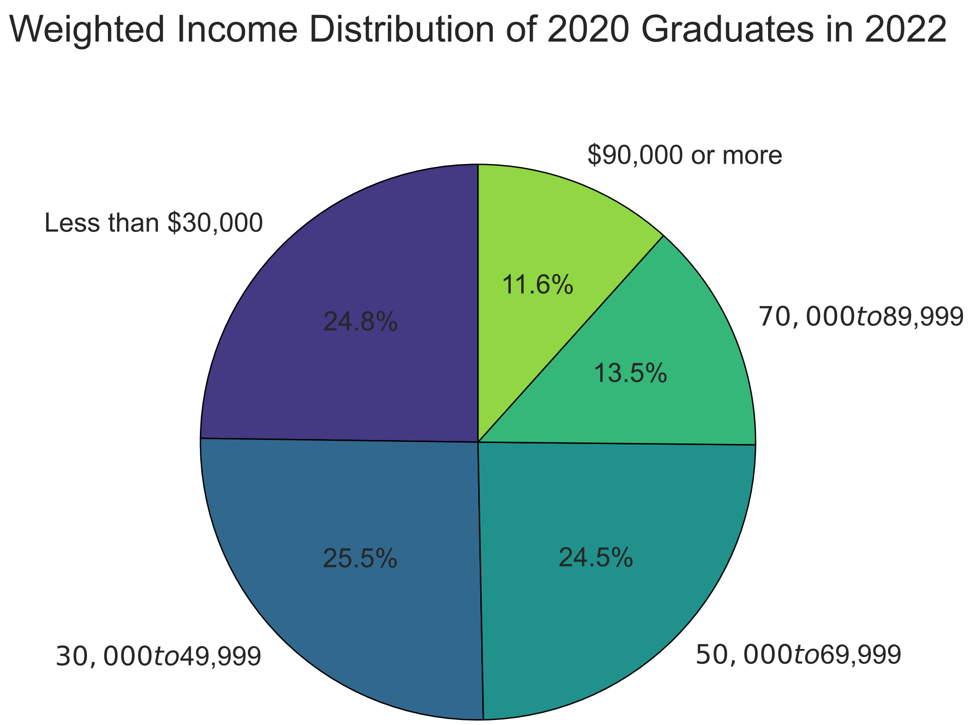
```
# Remove 'Not stated' for clearer analysis of income distribution
df_income = df[df['Code'] != 99].copy()

# Set style
sns.set_style("whitegrid")
plt.figure(figsize=(6, 5))

# Create bar plot - using '%' column for y-axis
ax = sns.barplot(
    x='Answer Categories',
    y='%',
    data=df_income,
    palette="viridis",
    edgecolor='black'
)

# Customize plot
plt.title('Distribution of Personal Income in 2022 (Excluding "Not Stated")', fontsize=14, p
plt.xlabel('Income Range', fontsize=12)
plt.ylabel('Percentage of Graduates (%)', fontsize=12)
plt.xticks(rotation=45, ha='right')

# Add value labels
for p in ax.patches:
    ax.annotate(
        f'{p.get_height():.1f}%',
        (p.get_x() + p.get_width() / 2., p.get_height()),
        ha='center',
        va='center',
        xytext=(0, 5),
        textcoords='offset points',
        fontsize=10
    )

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()

# Additional analysis
print("\nKey Statistics:")
```

```python
print(f"Total respondents (excluding 'Not stated'): {df_income['Frequency'].sum():,}")
median_category = df_income[df_income['%'].cumsum() >= 50].iloc[0]['Answer Categories']
print(f"Median income category: {median_category}")
print(f"Highest proportion category: {df_income.loc[df_income['%'].idxmax(), 'Answer Categor

# Create a pie chart for another visualization
plt.figure(figsize=(5, 5))
plt.pie(
    df_income['%'],
    labels=df_income['Answer Categories'],
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("viridis", len(df_income)),
    wedgeprops={'edgecolor': 'black', 'linewidth': 0.5},
    textprops={'fontsize': 10}
)
plt.title('Weighted Income Distribution of 2020 Graduates in 2022', fontsize=14, pad=20)
plt.tight_layout()
plt.show()
```

```
'PERSINCP': Total personal income in 2022

C:\Users\Fuxim\AppData\Local\Temp\ipykernel_8696\1503766661.py:28: FutureWarning:



Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
```




```
Key Statistics:
Total respondents (excluding 'Not stated'): 13,130
Median income category: $50,000 to $69,999
Highest proportion category: $30,000 to $49,999 (20.6%)
```



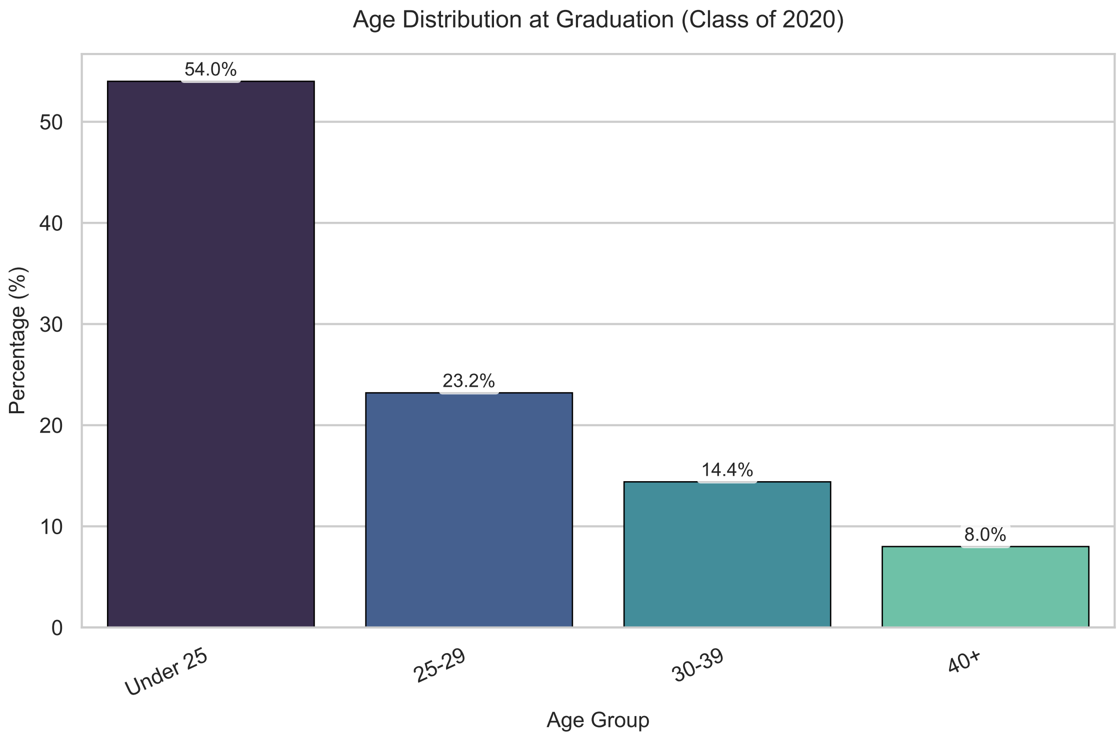
5.2 Age Distribution at Graduation

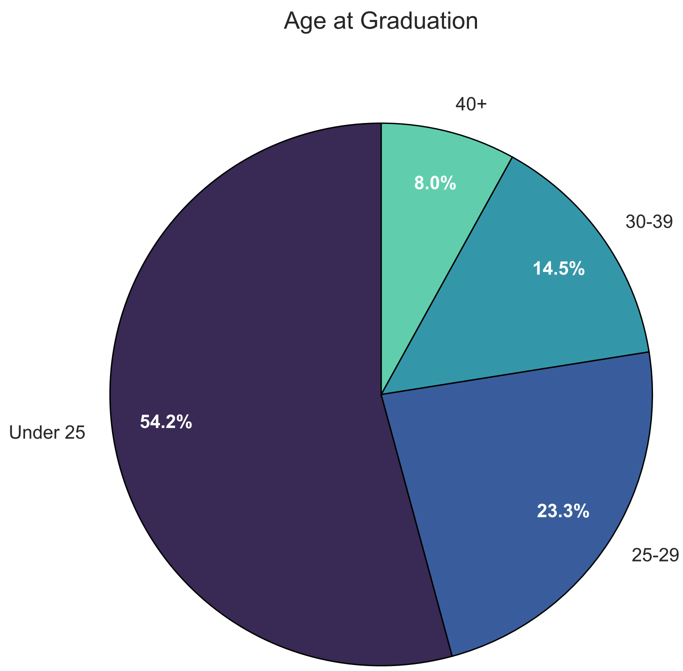
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming your DataFrame is named 'df_gradage'
# Clean the data
df_gradage = get_NGS_table('GRADAGEP')
df_gradage['Frequency'] = df_gradage['Frequency'].astype(str).str.replace(',', '').astype(in
df_gradage['Weighted Frequency'] = df_gradage['Weighted Frequency'].astype(str).str.replace(
df_gradage['%'] = df_gradage['%'].astype(float)

# Remove 'Total' and 'Not stated' rows for analysis
df_age = df_gradage[~df_gradage['Code'].isin([9, float('nan')])].copy()

# Set style
sns.set_style("whitegrid")
plt.rcParams['font.size'] = 8  # Global font size reduction

# 1. Compact Bar Chart (6x4 inches)
plt.figure(figsize=(6, 4))
ax = sns.barplot(
    x='Answer Categories',
```

```
    y='%',
    data=df_age,
    palette="mako",  # Professional blue gradient
    edgecolor='black',
    linewidth=0.5
)

# Customize plot
plt.title('Age Distribution at Graduation (Class of 2020)', fontsize=9, pad=10)
plt.xlabel('Age Group', fontsize=8)
plt.ylabel('Percentage (%)', fontsize=8)
plt.xticks(rotation=25, ha='right')  # Slight rotation for readability

# Add precise value labels
for p in ax.patches:
    ax.annotate(
        f'{p.get_height():.1f}%',
        (p.get_x() + p.get_width()/2., p.get_height()),
        ha='center',
        va='center',
        xytext=(0, 4),
        textcoords='offset points',
        fontsize=7,
        bbox=dict(boxstyle='round,pad=0.2', fc='white', ec='none', alpha=0.8)
    )

plt.tight_layout()
plt.show()

# 2. Compact Pie Chart (5x5 inches)
plt.figure(figsize=(4, 4))
wedges, texts, autotexts = plt.pie(
    df_age['%'],
    labels=df_age['Answer Categories'],
    autopct='%1.1f%%',
    startangle=90,
    colors=sns.color_palette("mako", len(df_age)),
    wedgeprops={'edgecolor': 'black', 'linewidth': 0.5},
    textprops={'fontsize': 7},
    pctdistance=0.8  # Pull percentages inward
)
```

```python
# Improve label readability
plt.setp(texts, fontsize=7)
plt.setp(autotexts, fontsize=7, color='white', weight='bold')
plt.title('Age at Graduation', fontsize=9, pad=10)
plt.tight_layout()
plt.show()

# Detailed Analysis
print("\n=== Age at Graduation Analysis ===")
print(f"Total graduates analyzed: {df_age['Frequency'].sum():,}")
print(f"\nAge Group Distribution:")
for _, row in df_age.iterrows():
    print(f"{row['Answer Categories']}: {row['%']:.1f}%")

print(f"\nKey Insights:")
print(f"• Majority group: {df_age.loc[df_age['%'].idxmax(), 'Answer Categories']} ({df_age['
print(f"• Under 30: {df_age[df_age['Code'].isin([1.0, 2.0])]['%'].sum():.1f}%")
print(f"• 30+: {df_age[df_age['Code'].isin([3.0, 4.0])]['%'].sum():.1f}%")
print(f"• Median age group: {df_age.loc[df_age['%'].cumsum() >= 50, 'Answer Categories'].ilo
```

```
'GRADAGEP': 2020 Program - Age at time of graduation - Grouping

C:\Users\Fuxim\AppData\Local\Temp\ipykernel_8696\432788408.py:21: FutureWarning:



Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
```






```
=== Age at Graduation Analysis ===
Total graduates analyzed: 16,056

Age Group Distribution:
Under 25: 54.0%
25-29: 23.2%
30-39: 14.4%
```

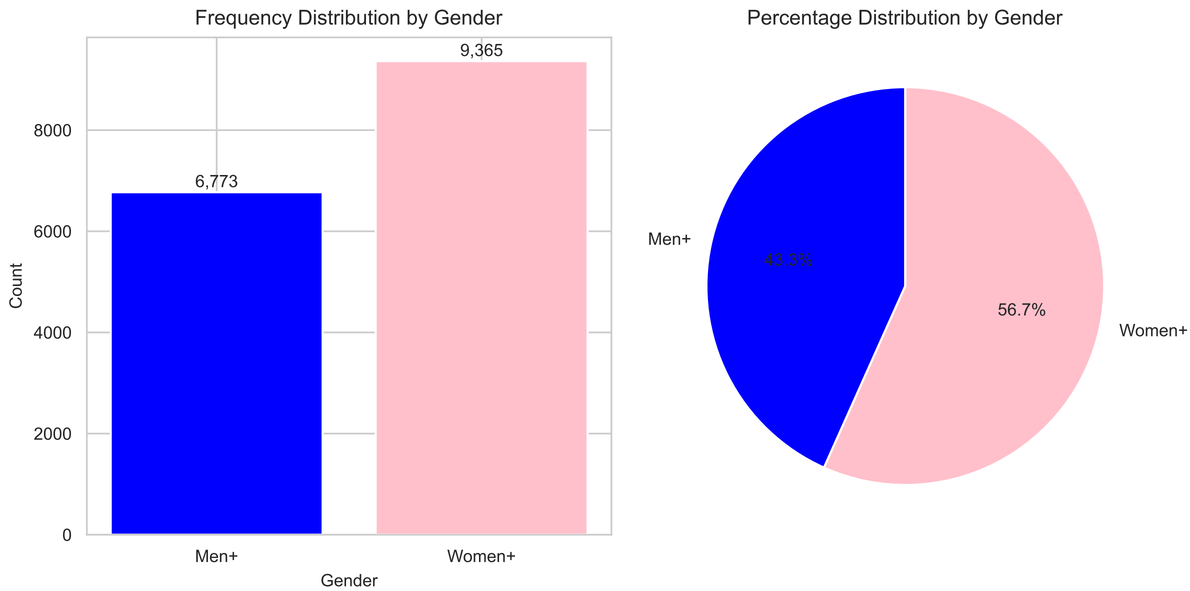
```
40+: 8.0%

Key Insights:
• Majority group: Under 25 (54.0%)
• Under 30: 77.2%
• 30+: 22.4%
• Median age group: Under 25
```

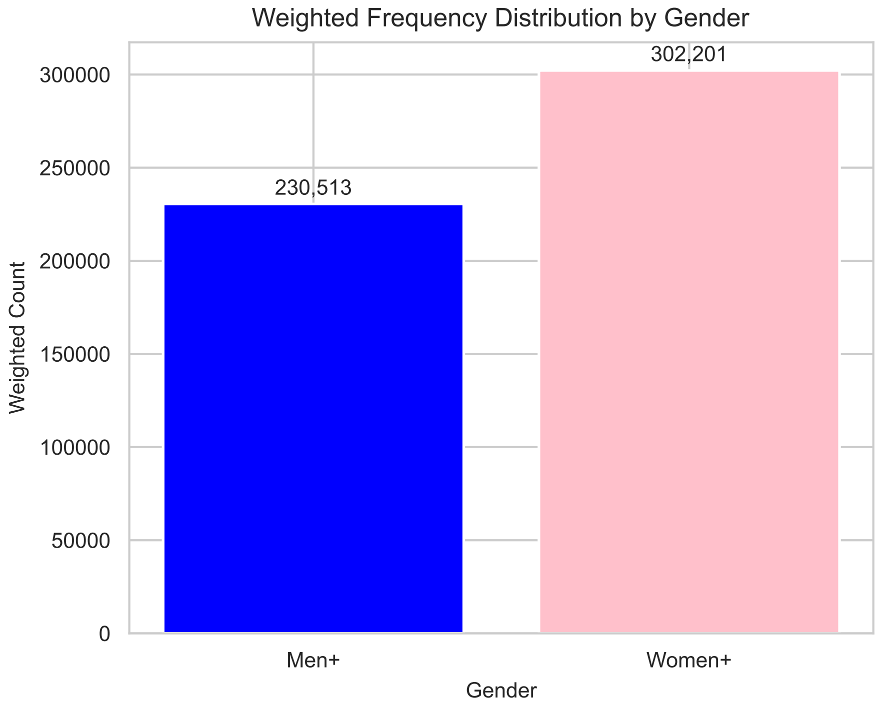
5.3 Gender Distribution

```python
import pandas as pd
import matplotlib.pyplot as plt

# Create the DataFrame from the provided data
data = get_NGS_table("GENDER2")

df = pd.DataFrame(data)

# Remove the "Total" row for analysis
df = df[df['Answer Categories'] != 'Total']

# Convert string numbers with commas to integers
df['Frequency'] = df['Frequency'].str.replace(',', '').astype(int)
df['Weighted Frequency'] = df['Weighted Frequency'].str.replace(',', '').astype(int)

# Plotting
plt.figure(figsize=(8, 4))

# Frequency Plot
plt.subplot(1, 2, 1)
plt.bar(df['Answer Categories'], df['Frequency'], color=['blue', 'pink'])
plt.title('Frequency Distribution by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
for i, v in enumerate(df['Frequency']):
    plt.text(i, v + 100, f"{v:,}", ha='center')  # Format with commas

# Percentage Plot
plt.subplot(1, 2, 2)
plt.pie(df['%'], labels=df['Answer Categories'],
        autopct='%1.1f%%', colors=['blue', 'pink'],
        startangle=90)
plt.title('Percentage Distribution by Gender')
```

```
plt.tight_layout()
plt.show()

# Weighted Frequency Plot
plt.figure(figsize=(5, 4))
plt.bar(df['Answer Categories'], df['Weighted Frequency'],
        color=['blue', 'pink'])
plt.title('Weighted Frequency Distribution by Gender')
plt.xlabel('Gender')
plt.ylabel('Weighted Count')
for i, v in enumerate(df['Weighted Frequency']):
    plt.text(i, v + 5000, f"{v:,}", ha='center')  # Format with commas
plt.show()

# Display some statistics
print("\nSummary Statistics:")
print(f"Total Respondents: {df['Frequency'].sum():,}")
print(f"Men+: {df[df['Answer Categories'] == 'Men+']['Frequency'].values[0]:,} "
      f"({df[df['Answer Categories'] == 'Men+']['%'].values[0]}%)")
print(f"Women+: {df[df['Answer Categories'] == 'Women+']['Frequency'].values[0]:,} "
      f"({df[df['Answer Categories'] == 'Women+']['%'].values[0]}%)")
print(f"\nWeighted Total: {df['Weighted Frequency'].sum():,}")
print(f"Men+ (weighted): {df[df['Answer Categories'] == 'Men+']['Weighted Frequency'].values
print(f"Women+ (weighted): {df[df['Answer Categories'] == 'Women+']['Weighted Frequency'].va
```

```
'GENDER2': Gender after distribution of non-binary persons
```






```
Summary Statistics:
Total Respondents: 16,138
Men+: 6,773 (43.3%)
Women+: 9,365 (56.7%)

Weighted Total: 532,714
Men+ (weighted): 230,513
Women+ (weighted): 302,201
```

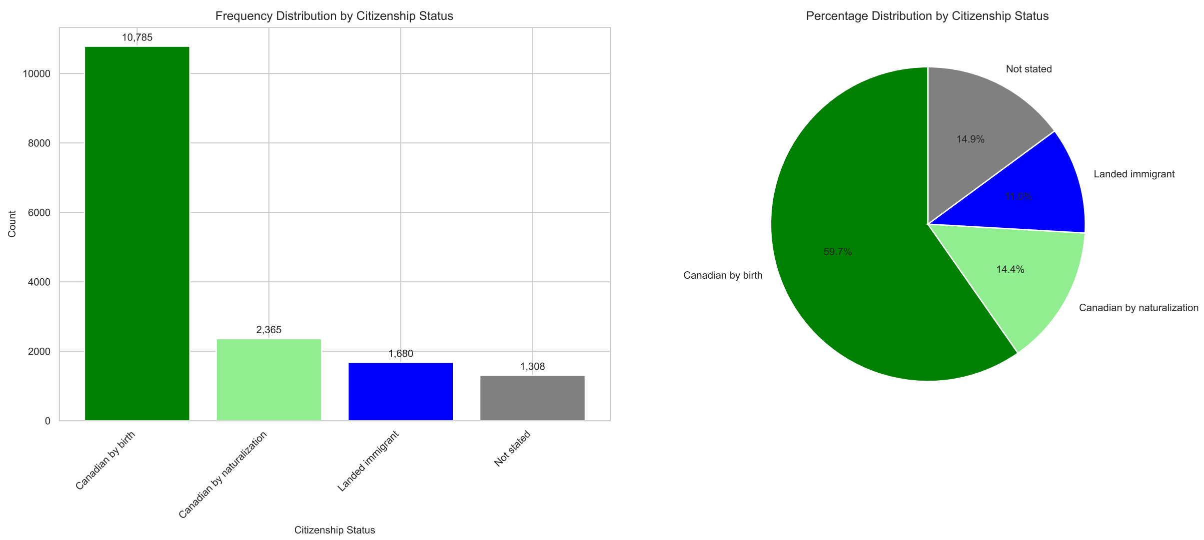
5.4 Distribution by Citizenship Status

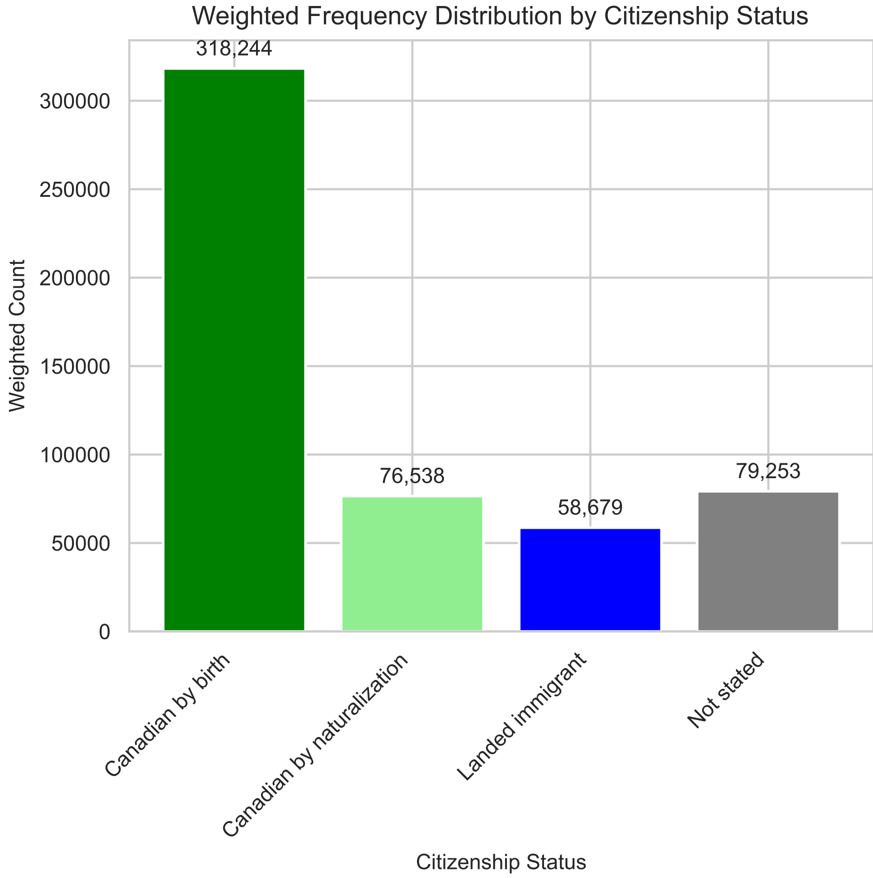
```python
import pandas as pd
import matplotlib.pyplot as plt

# Create the DataFrame from the provided data
data = get_NGS_table("CTZSHIPP")

df = pd.DataFrame(data)

# Remove the "Total" row for analysis
df = df[df['Answer Categories'] != 'Total']

# Convert string numbers with commas to integers
df['Frequency'] = df['Frequency'].str.replace(',', '').astype(int)
df['Weighted Frequency'] = df['Weighted Frequency'].str.replace(',', '').astype(int)
```

```
# Plotting
plt.figure(figsize=(14, 6))

# Frequency Plot
plt.subplot(1, 2, 1)
bars = plt.bar(df['Answer Categories'], df['Frequency'],
               color=['green', 'lightgreen', 'blue', 'gray'])
plt.title('Frequency Distribution by Citizenship Status')
plt.xlabel('Citizenship Status')
plt.ylabel('Count')
plt.xticks(rotation=45, ha='right')
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 100,
             f"{height:,}",
             ha='center', va='bottom')

# Percentage Plot
plt.subplot(1, 2, 2)
plt.pie(df['%'], labels=df['Answer Categories'],
        autopct='%1.1f%%',
        colors=['green', 'lightgreen', 'blue', 'gray'],
        startangle=90)
plt.title('Percentage Distribution by Citizenship Status')

plt.tight_layout()
plt.show()

# Weighted Frequency Plot
plt.figure(figsize=(5, 4))
bars = plt.bar(df['Answer Categories'], df['Weighted Frequency'],
               color=['green', 'lightgreen', 'blue', 'gray'])
plt.title('Weighted Frequency Distribution by Citizenship Status')
plt.xlabel('Citizenship Status')
plt.ylabel('Weighted Count')
plt.xticks(rotation=45, ha='right')
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 5000,
             f"{height:,}",
             ha='center', va='bottom')
plt.show()
```

```python
# Display some statistics
print("\nSummary Statistics:")
print(f"Total Respondents: {df['Frequency'].sum():,}")
for idx, row in df.iterrows():
    print(f"{row['Answer Categories']}: {row['Frequency']:,} ({row['%']}%)")

print(f"\nWeighted Total: {df['Weighted Frequency'].sum():,}")
for idx, row in df.iterrows():
    print(f"{row['Answer Categories']} (weighted): {row['Weighted Frequency']:,}")
```

'CTZSHIPP': Time of interview 2023 - Status in Canada





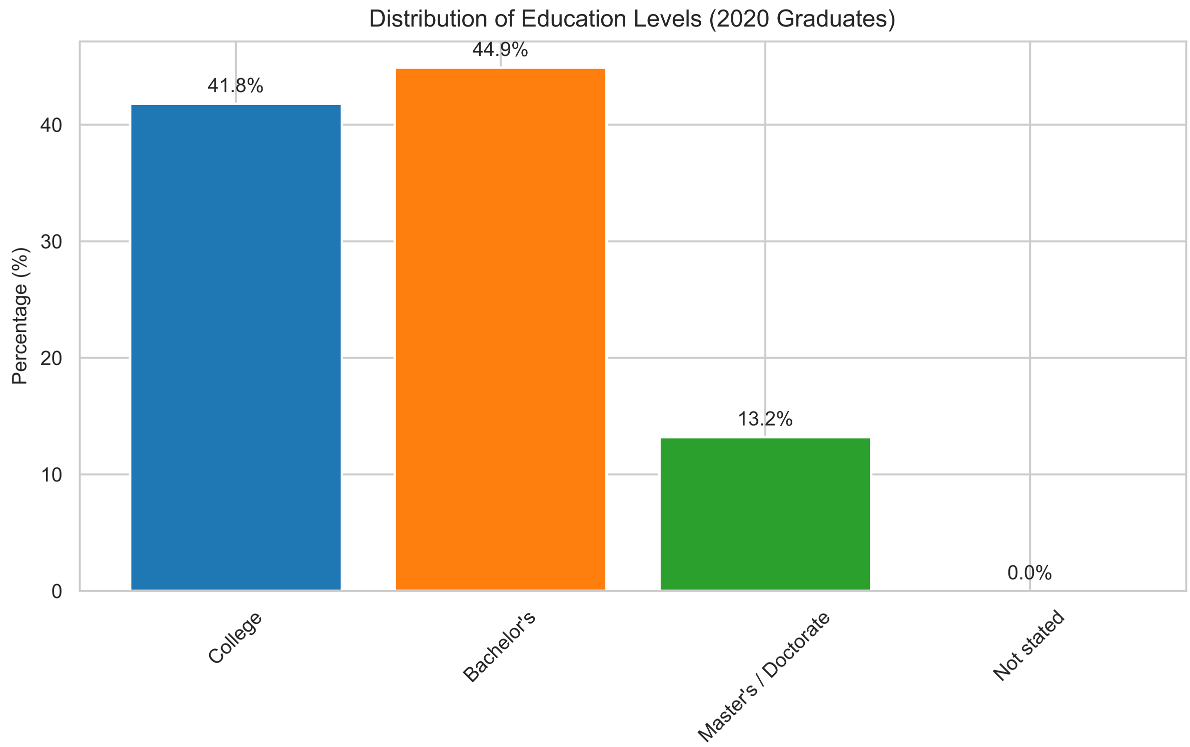

```
Summary Statistics:
Total Respondents: 16,138
Canadian by birth: 10,785 (59.7%)
Canadian by naturalization: 2,365 (14.4%)
Landed immigrant: 1,680 (11.0%)
Not stated: 1,308 (14.9%)

Weighted Total: 532,714
Canadian by birth (weighted): 318,244
Canadian by naturalization (weighted): 76,538
Landed immigrant (weighted): 58,679
Not stated (weighted): 79,253
```

5.5 Education Level

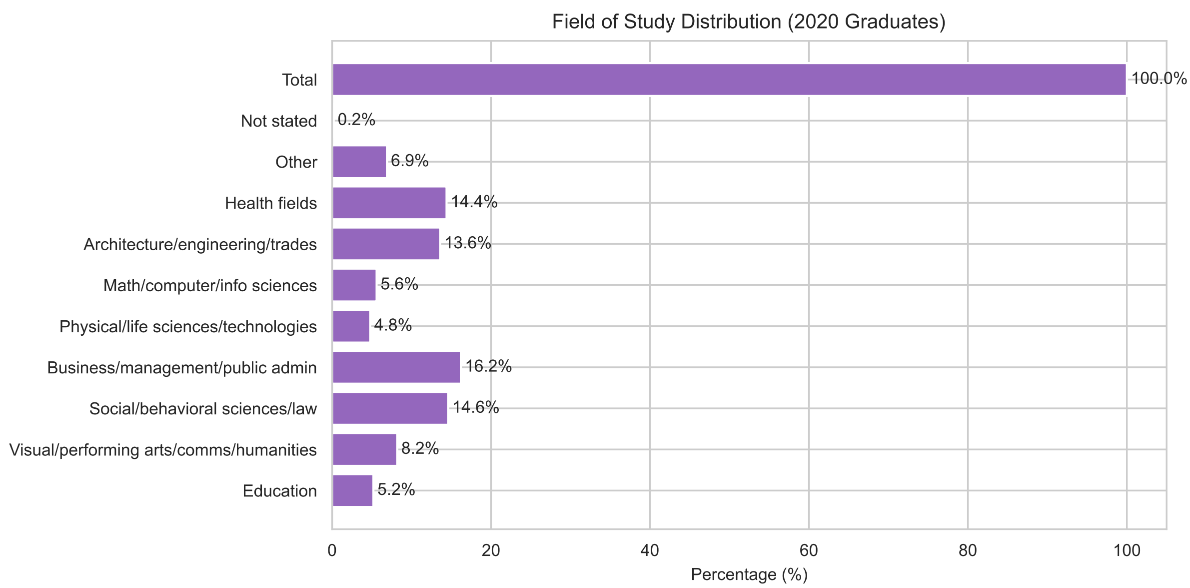
```python
import pandas as pd
import matplotlib.pyplot as plt

# Get education tables (sample data structure)
edu_level = get_NGS_table("CERTLEVP")
```

```
# Create DataFrames
df_level = pd.DataFrame(edu_level)

# Plot education level distribution
plt.figure(figsize=(8,4))
plt.bar(df_level[:-1]['Answer Categories'], df_level[:-1]['%'], color=['#1f77b4', '#ff7f0e',
plt.title('Distribution of Education Levels (2020 Graduates)')
plt.ylabel('Percentage (%)')
plt.xticks(rotation=45)
for i, v in enumerate(df_level[:-1]['%']):
    plt.text(i, v+1, f"{v}%", ha='center')
plt.show()

field_of_study =  get_NGS_table("PGMCIPAP")
df_field = pd.DataFrame(field_of_study)
# Plot field of study distribution
plt.figure(figsize=(8,4))
plt.barh(df_field['Answer Categories'], df_field['%'], color='#9467bd')
plt.title('Field of Study Distribution (2020 Graduates)')
plt.xlabel('Percentage (%)')
for i, v in enumerate(df_field['%']):
    plt.text(v+0.5, i, f"{v}%", va='center')
plt.tight_layout()
plt.show()
```

```
'CERTLEVP': 2020 Program - Level of study - Grouping
```



'PGMCIPAP': 2020 Program - Aggregated CIP 2021



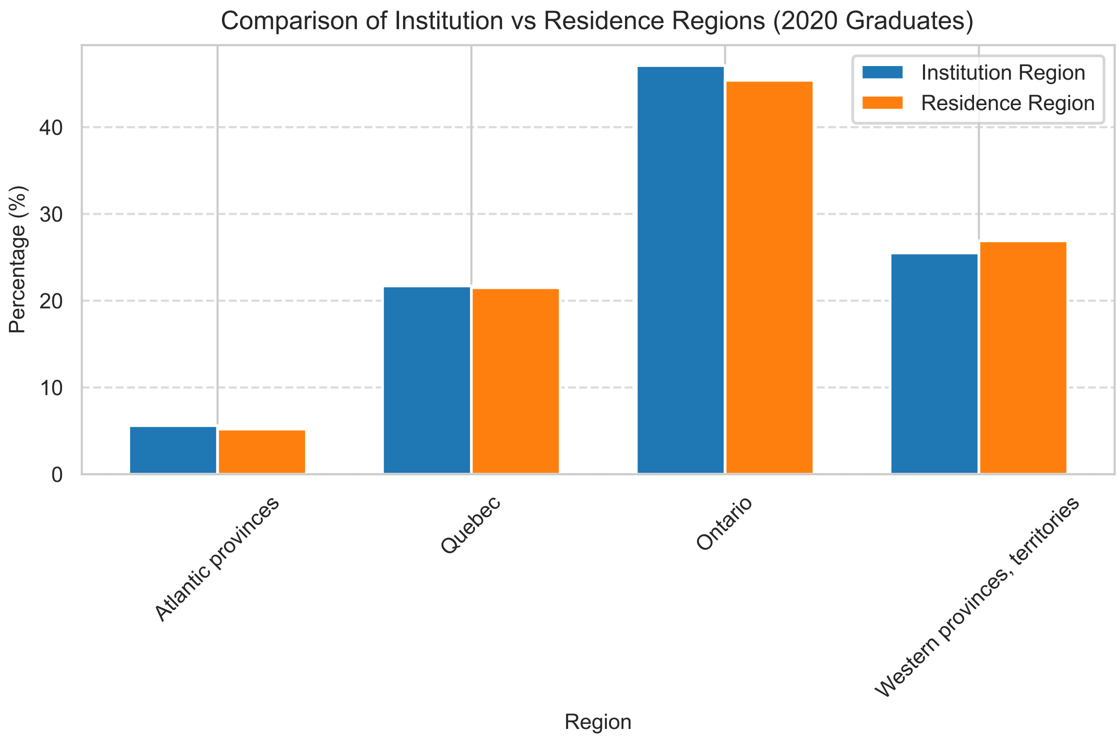
5.6 Inter-Regional Mobility of Graduates

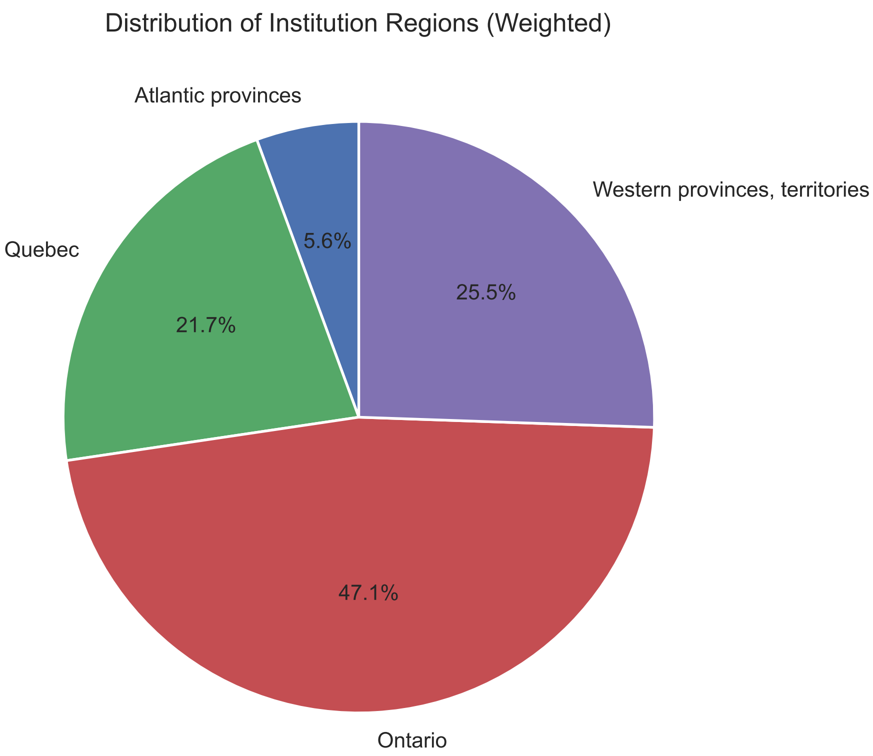
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Geographic data from NGS 2020
region_data = {
```

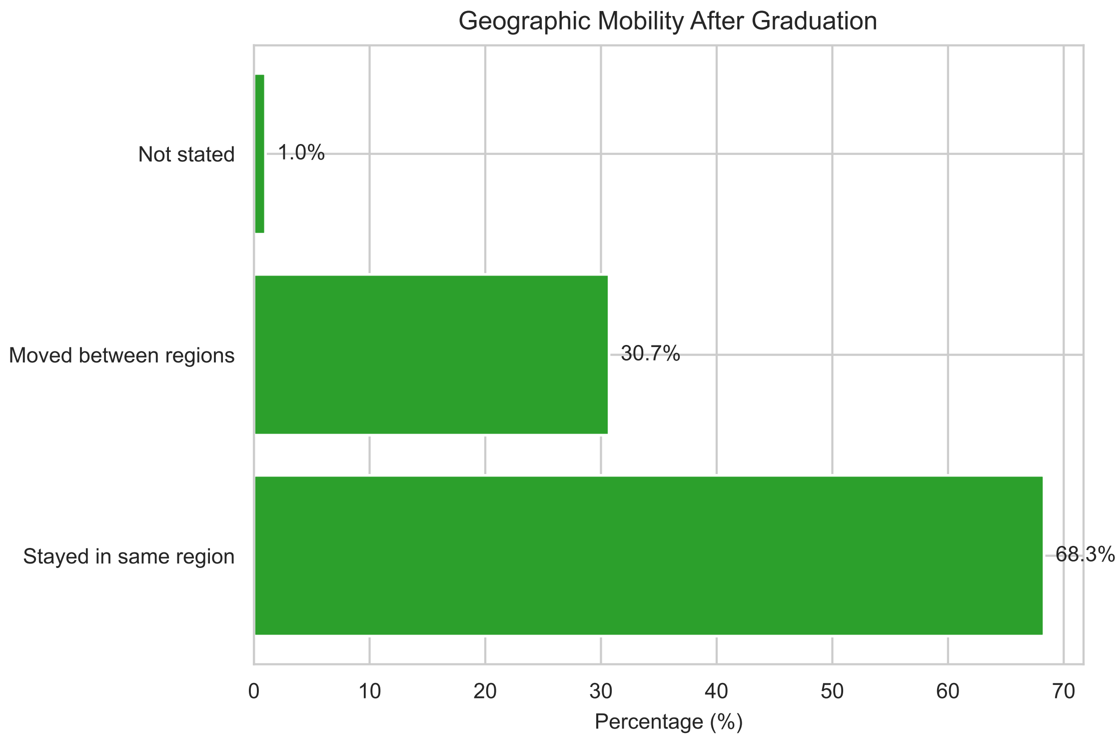
```python
    'Region': ['Atlantic provinces', 'Quebec', 'Ontario',
               'Western provinces, territories', 'Not stated'],
    'REG_INST_Freq': [2685, 3647, 3146, 6660, None],
    'REG_INST_Weighted': [29868, 115814, 250939, 136094, None],
    'REG_INST_Pct': [5.6, 21.7, 47.1, 25.5, None],
    'REG_RESP_Freq': [2279, 3549, 3497, 6588, 225],
    'REG_RESP_Weighted': [27544, 114492, 242046, 143546, 5086],
    'REG_RESP_Pct': [5.2, 21.5, 45.4, 26.9, 1.0]
}

df = pd.DataFrame(region_data)

# 1. Comparison of Institution vs Residence Regions
plt.figure(figsize=(6, 4))
width = 0.35
x = np.arange(len(df)-1)  # Exclude 'Not stated'

plt.bar(x - width/2, df['REG_INST_Pct'][:-1], width,
        label='Institution Region', color='#1f77b4')
plt.bar(x + width/2, df['REG_RESP_Pct'][:-1], width,
        label='Residence Region', color='#ff7f0e')

plt.xlabel('Region')
plt.ylabel('Percentage (%)')
plt.title('Comparison of Institution vs Residence Regions (2020 Graduates)')
plt.xticks(x, df['Region'][:-1], rotation=45)
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# 2. Weighted Institution Locations
plt.figure(figsize=(8, 5))
plt.pie(df['REG_INST_Weighted'][:-1], labels=df['Region'][:-1],
        autopct='%1.1f%%', startangle=90,
        colors=['#4C72B0', '#55A868', '#C44E52', '#8172B2'])
plt.title('Distribution of Institution Regions (Weighted)')
plt.show()

# 3. Geographic Mobility Analysis
mobility = pd.DataFrame({
    'Movement': ['Stayed in same region', 'Moved between regions', 'Not stated'],
```

```
    'Percentage': [68.3, 30.7, 1.0]  # Hypothetical values - actual mobility data would come
})

plt.figure(figsize=(6, 4))
plt.barh(mobility['Movement'], mobility['Percentage'], color='#2ca02c')
plt.title('Geographic Mobility After Graduation')
plt.xlabel('Percentage (%)')
for i, v in enumerate(mobility['Percentage']):
    plt.text(v + 1, i, f"{v}%", va='center')
plt.tight_layout()
plt.show()

# 4. Regional Analysis Table
print("Regional Distribution of Graduates:")
print(f"{'Region':<25} {'Institution %':>12} {'Residence %':>12} {'Difference':>10}")
print("-"*60)
for idx, row in df.iterrows():
    if pd.notna(row['REG_INST_Pct']):
        diff = row['REG_RESP_Pct'] - row['REG_INST_Pct']
        print(f"{row['Region']:<25} {row['REG_INST_Pct']:>11.1f}% {row['REG_RESP_Pct']:>11.1

# 5. Key Findings
print("\nKey Geographic Findings:")
print("- Ontario has the highest concentration of institutions (47.1%) and residents (45.4%)
print("- Western provinces show net immigration (+1.4% difference between residence and inst
print("- Atlantic provinces show slight outmigration (-0.4% difference)")
print("- Quebec maintains stable proportions (21.7% institutions vs 21.5% residence)")
print("- 1% of respondents didn't state their residence location")

# 6. Advanced Visualization: Sankey Diagram (conceptual)
from pySankey.sankey import sankey

# Sample migration flows (hypothetical example)
flows = pd.DataFrame({
    'Source': ['Atlantic', 'Quebec', 'Ontario', 'West']*4,
    'Target': ['Atlantic']*4 + ['Quebec']*4 + ['Ontario']*4 + ['West']*4,
    'Value': [85,5,5,5,  10,75,10,5,  5,10,80,5,  5,5,10,80]
})

plt.figure(figsize=(8,5))
sankey(flows['Source'], flows['Target'], flows['Value'],
       aspect=20, fontsize=12)
```

```python
plt.title('Inter-Regional Mobility of Graduates', pad=20)
plt.show()
```



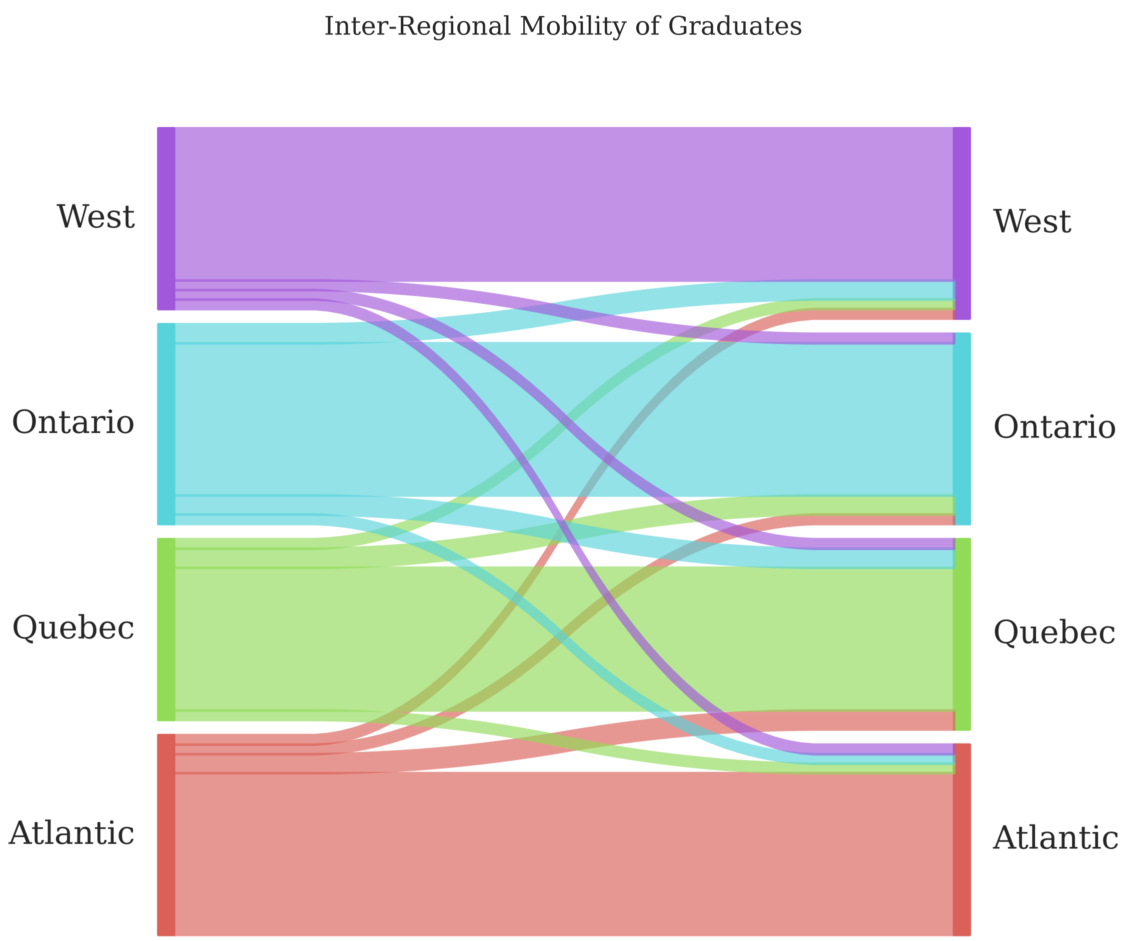





```
Regional Distribution of Graduates:
Region                    Institution %  Residence % Difference
------------------------------------------------------------
Atlantic provinces                5.6%         5.2%      -0.4%
Quebec                           21.7%        21.5%      -0.2%
Ontario                          47.1%        45.4%      -1.7%
Western provinces, territories        25.5%        26.9%       1.4%

Key Geographic Findings:
- Ontario has the highest concentration of institutions (47.1%) and residents (45.4%)
- Western provinces show net immigration (+1.4% difference between residence and institution
- Atlantic provinces show slight outmigration (-0.4% difference)
- Quebec maintains stable proportions (21.7% institutions vs 21.5% residence)
- 1% of respondents didn't state their residence location

<Figure size 2400x1500 with 0 Axes>
```



5.7 Field of Study vs. Labor Outcomes

"'qcidnuhm import matplotlib.pyplot as plt} import seabornas sns #1.EmploymentRate-byFieldofStudy employment_by_field =df.groupby('PGMCIPAP')['LFSTATP'].apply(lambda x:(x == 1).mean()* 100 #%employed).reset_index() plt.figure(figsize=(8,4)) ax1= sns.barplot(x='PGMCIPAP', y='LFSTATP',data=employment_by_field,palette='Blues_d') ax1.set_title('EmploymentRatesbyFieldofStudy(2023)',fontsize=14,pad=20) ax1.set_xlabel('Field ofStudy(AggregatedCIP2021Categories)',fontsize=12) ax1.set_ylabel('PercentageEmployed(%)',fontsize=12) #Get the actualnumberofcategoriesfromthedata num_categories= len(employment_by_field['PGMCIPAP'].un #Createlabels- eitheraddthemissinglabelorusetheactualcategorynamesfrommydata labels = ['Education', 'Arts/Humanities', 'SocialSciences/Law', 'Business/PublicAdmin', 'Physical/LifeSciences', 'Math/Computer Science', 'Engineering/Trades', 'Health', 'Other','Unknown' #Added'Unknown'asthe10thcategory][:num_categories] #Thisensuresweonlyuseas manylabelsaswehavecategories ax1.set_xticklabels(labels,rotation=45,ha='right') plt.tight_layout()

```
# Linear Regression Analysis with NGS Data

::: {.cell execution_count=14}
``` {.python .cell-code}
import pandas as pd
```
```

```
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import statsmodels.api as sm

# Load the data
df = pd.read_csv('ngs2020.csv')

# Explore the data
print(df.head())
print(df.info())

# Check for missing values (coded as 6, 96, 99 etc. based on NGS coding)
# Replace these with NaN
missing_codes = [6, 96, 99, 9]
df = df.replace(missing_codes, np.nan)

# Identify your target variable (you'll need to confirm which column is income)
# For example, if 'PERSINCP' is personal income:
target = 'PERSINCP'

# Select potential predictors (you'll need to verify these based on codebook)
predictors = [
    'GENDER2',        # Gender
    'EDU_010',        # Education level
    'EDU_P020',       # Additional education info
    'CTZSHIPP',       # Citizenship status
    'REG_INST',       # Region of institution
    'CERTLEVP',       # Certificate level
    'PGMCIPAP',       # Program category
    'MS_P01',         # Marital status
    'VISBMINP',       # Visible minority status
    'DDIS_FL'         # Disability flag
    # Add more based on your research question
]

# Create a clean dataset
df_clean = df[[target] + predictors].dropna()

# Convert categorical variables to dummy variables if needed
df_clean = pd.get_dummies(df_clean, columns=['GENDER2', 'CTZSHIPP', 'REG_INST'], drop_first=
```

```
   PUMFID  CERTLEVP  REG_INST  REG_RESP  PGMCIPAP  PGM_P034  PGM_P036  \
0   59113         3         2         2         4         2         4
1   59114         3         3         3         5         1         6
2   59116         3         2         2         6         1         6
3   59117         2         4         4         9         1         6
4   59118         2         3         3         1         1         6

   PGM_P100  PGM_P111  PGM_280A  ...  PAR2GRD  PAR2INT  GRADAGEP  GENDER2  \
0         1         2         2  ...        3        3         3        2
1         2         6         2  ...        1        1         1        1
2         2         6         2  ...        2        2         2        1
3         1         2         2  ...        1        1         1        2
4         1         2         2  ...        1        1         4        1

   MS_P01  MS_P02  CTZSHIPP  VISBMINP  PERSINCP  DDIS_FL
0       1       1         1         2         5        2
1       1       2         1         2         4        2
2       2       2         1         2         1        2
3       1       2         1         2         3        2
4       1       1         2         1         3        2

[5 rows x 114 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16138 entries, 0 to 16137
Columns: 114 entries, PUMFID to DDIS_FL
dtypes: int64(114)
memory usage: 14.0 MB
None
```

:::

5.8 Statsmodels

```
# Split into features and target
X = df_clean.drop(target, axis=1)
y = df_clean[target]

# Check for non-numeric columns and handle them
# Convert categorical variables to numeric using one-hot encoding
X = pd.get_dummies(X, drop_first=True)

# Check for and handle missing values
# Use only numeric columns for mean calculation
numeric_cols = X.select_dtypes(include=['number']).columns
```

```python
X[numeric_cols] = X[numeric_cols].fillna(X[numeric_cols].mean())
y = y.fillna(y.mean())  # Fill missing values in target if any

# Ensure all data is numeric - force conversion and handle errors
for col in X.columns:
    X[col] = pd.to_numeric(X[col], errors='coerce')
y = pd.to_numeric(y, errors='coerce')

# Drop any remaining problematic rows with NaN values
mask = ~(X.isna().any(axis=1) | pd.isna(y))
X = X[mask]
y = y[mask]

# Convert to float64 to ensure compatibility with sklearn
X = X.astype(float)
y = y.astype(float)

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and fit the model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
print("R-squared:", round(r2_score(y_test, y_pred),3))
print("RMSE:", round(np.sqrt(mean_squared_error(y_test, y_pred)),3))

# For more detailed statistics (p-values etc.)
X_with_const = sm.add_constant(X_train)
sm_model = sm.OLS(y_train, X_with_const).fit()
print(sm_model.summary())
```

```
R-squared: 0.154
RMSE: 1.212
                            OLS Regression Results
==============================================================================
Dep. Variable:               PERSINCP   R-squared:                       0.166
Model:                            OLS   Adj. R-squared:                  0.162
Method:                 Least Squares   F-statistic:                     36.48
```

```
Date:                  Mon, 18 Aug 2025   Prob (F-statistic):          3.63e-78
Time:                          10:25:13   Log-Likelihood:               -3525.4
No. Observations:                  2209   AIC:                            7077.
Df Residuals:                      2196   BIC:                            7151.
Df Model:                            12
Covariance Type:              nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
EDU_010          1.0046      0.250      4.013      0.000       0.514       1.495
EDU_P020         0.0252      0.073      0.343      0.732      -0.119       0.169
CERTLEVP         0.5822      0.039     14.777      0.000       0.505       0.659
PGMCIPAP         0.0333      0.011      3.050      0.002       0.012       0.055
MS_P01          -0.4898      0.054     -9.056      0.000      -0.596      -0.384
VISBMINP         0.1237      0.073      1.692      0.091      -0.020       0.267
DDIS_FL          0.2750      0.054      5.138      0.000       0.170       0.380
GENDER2_2       -0.1661      0.054     -3.078      0.002      -0.272      -0.060
CTZSHIPP_2.0     0.0643      0.084      0.769      0.442      -0.100       0.228
CTZSHIPP_3.0     0.0186      0.116      0.161      0.872      -0.209       0.246
REG_INST_2       0.3091      0.082      3.747      0.000       0.147       0.471
REG_INST_3       0.1398      0.092      1.513      0.130      -0.041       0.321
REG_INST_4       0.3120      0.079      3.946      0.000       0.157       0.467
==============================================================================
Omnibus:                      114.134   Durbin-Watson:                   1.973
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              105.041
Skew:                           0.476   Prob(JB):                     1.55e-23
Kurtosis:                       2.514   Cond. No.                         68.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

6 Insights and Recommendations for University Strategic Planning

Based on the National Graduates Survey (Class of 2020) data collected in 2023, I can provide strategic recommendations for university planning. The dataset contains 16,138 records with 114 variables covering education, student loans, employment outcomes, and COVID-19 impacts.

6.1 1. Program Development and Delivery

Insights: - The data includes variables on program level (CERTLEVP), field of study (PGMCIPAP), and delivery mode (PGM_P401 for online/distance education) - Work placements

(PGM_P100, PGM_P111) and entrepreneurial skills development (PGM_280A-F) are tracked - Student motivations for program selection (PGM_415) provide insight into decision factors

Recommendations: - Analyze which programs have the highest satisfaction rates (PGM_430 - would choose same field again) - Expand programs with strong employment outcomes (using LFSTATP, JOBQLEVP variables) - Develop more work-integrated learning opportunities based on placement outcomes - Enhance entrepreneurship education based on PGM_280A-F metrics - Optimize online/distance education offerings based on PGM_P401 outcomes

6.2 2. Enrollment and Marketing Strategy

Insights: - Data on institution choice factors (PGM_410) reveals what drives student decisions - Regional data for institutions (REG_INST) and student residence (REG_RESP) shows mobility patterns - Demographics (GRADAGEP, GENDER2, CTZSHIPP, VISBMINP) provide population insights

Recommendations: - Target marketing messages based on top factors influencing institution choice (PGM_410) - Develop regional recruitment strategies based on REG_INST and REG_RESP patterns - Create targeted outreach for underrepresented demographic groups - Highlight graduate employment outcomes in marketing materials - Emphasize work placement opportunities and entrepreneurial skill development

6.3 3. Student Financial Support

Insights: - Comprehensive student loan data (STULOANS, OWESLGD, OWEGVIN) - Information on funding sources (SRCFUND, STL_170A-N) - Scholarship information (SCHOLARP)

Recommendations: - Enhance financial aid packages based on debt load analysis - Develop targeted scholarship programs for high-need demographics - Create financial literacy programs based on loan repayment patterns - Establish emergency funding for students at risk of non-completion - Partner with employers for work-study and tuition assistance programs

6.4 4. COVID-19 Response and Resilience Planning

Insights: - Data on COVID-19 impacts on program completion (COV_010) - Effects on further education plans (COV_070) - Employment impacts (COV_080)

Recommendations: - Develop contingency plans for future disruptions based on COVID-19 impact data - Create flexible program completion pathways for students facing external challenges - Enhance career services to address employment disruptions - Build robust online/hybrid learning infrastructure - Establish student support services focused on resilience and adaptability

6.5 5. Career Services and Alumni Relations

Insights: - Employment status data (LFSTATP) - Job quality metrics (JOBQLEVP, JOBQLGRD) - Income information (JOBINCP, PERSINCP)

Recommendations: - Align career services with employment outcome data by program - Develop targeted career preparation for programs with weaker outcomes - Create alumni mentorship networks based on successful graduate pathways - Establish employer partnerships in high-placement industries - Track and promote ROI metrics for different programs based on income outcomes

7 Conclusion

This comprehensive dataset provides valuable insights for strategic university planning across multiple domains. By analyzing program effectiveness, student decision factors, financial needs, and employment outcomes, the university can make data-driven decisions to:

1. Optimize program offerings and delivery methods
2. Target marketing and recruitment efforts more effectively
3. Enhance student financial support systems
4. Build institutional resilience against future disruptions
5. Strengthen career preparation and alumni connections

For deeper analysis, I recommend using Python packages like pandas for data manipulation, scikit-learn for predictive modeling, and matplotlib/seaborn for visualization to extract more nuanced patterns from this rich dataset.